Artificial Neural Networks for Renewable Energy Systems

Yurii Bobechko
Lviv Polytechnic National University

Cooperation of Universities in Central and Eastern Europe - CUCEE, 2025

Agenda

01

Introduction

02

Fundamentals of Artificial Neural Networks

Terminology, Basic Architecture of Artificial Neural Networks, Activation Functions, Architecture Types, Types of Learning, Key Training Concepts

03

Renewable Energy Systems

Types of Renewable Energy Sources, Trends in Renewable Energy, Challenges Addressable by ANNs

04

ANNs for Renewable Energy

Energy Forecasting, Fault Detection and Diagnostics, Additional Applications, Hybrid and Ensemble Approaches

05

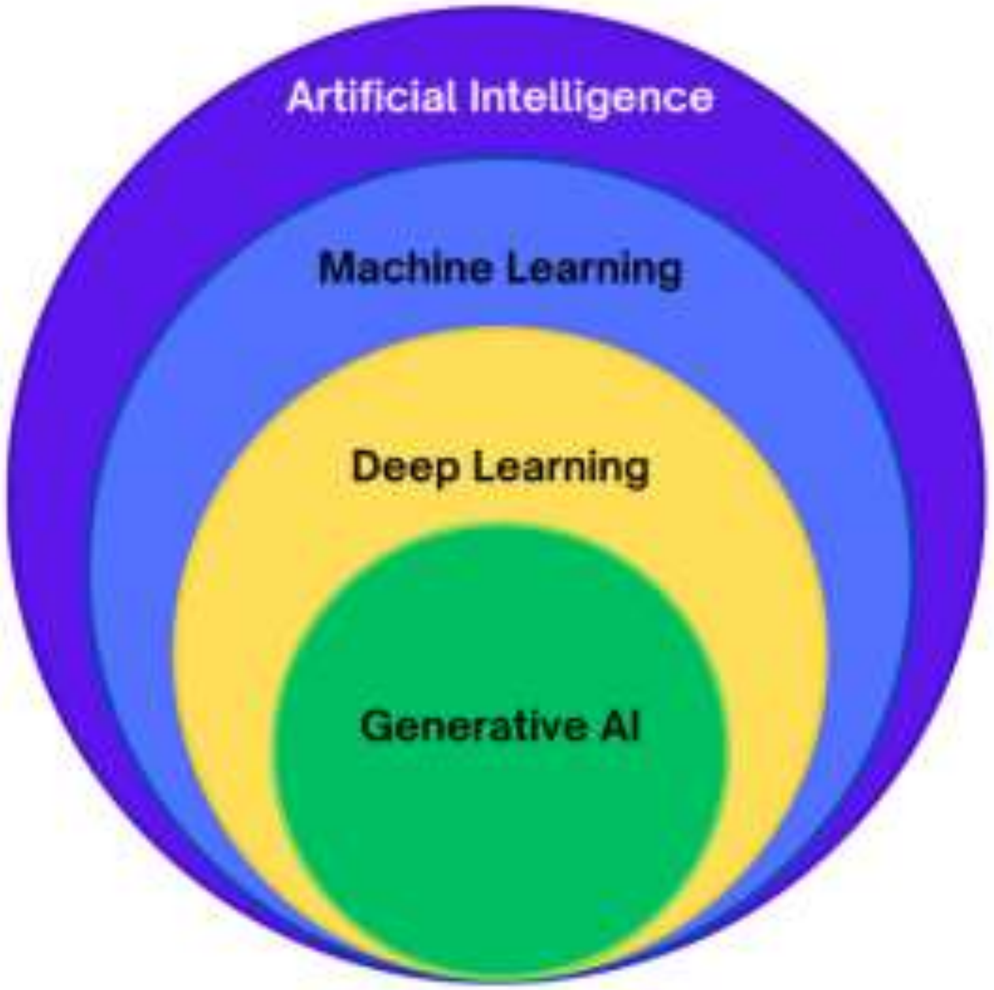
Real World Applications

DeepMind, Siemens Gamesa, and SPIC

06

Conclusions

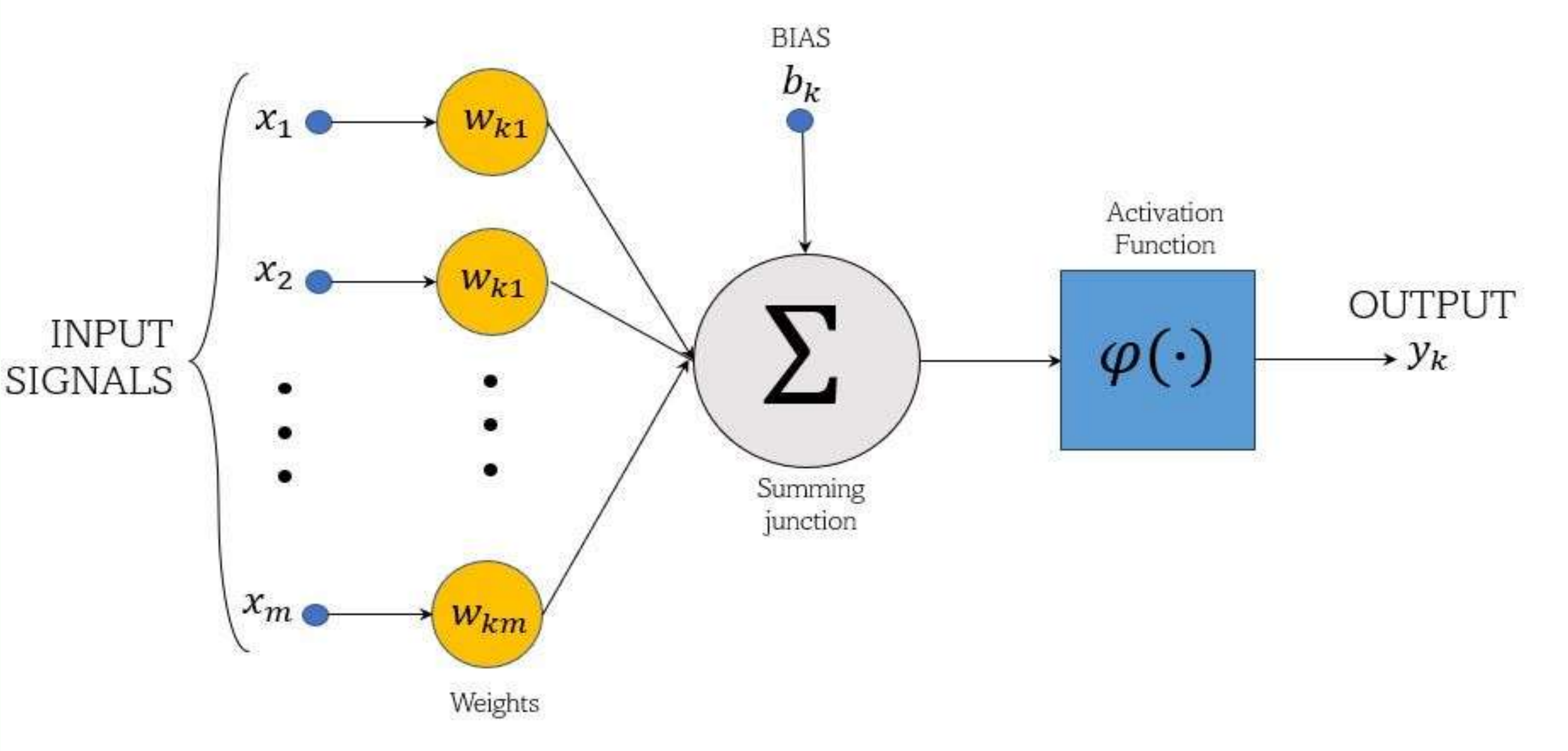
Terminology: AI, ML, DL, Generative AI, ANNs

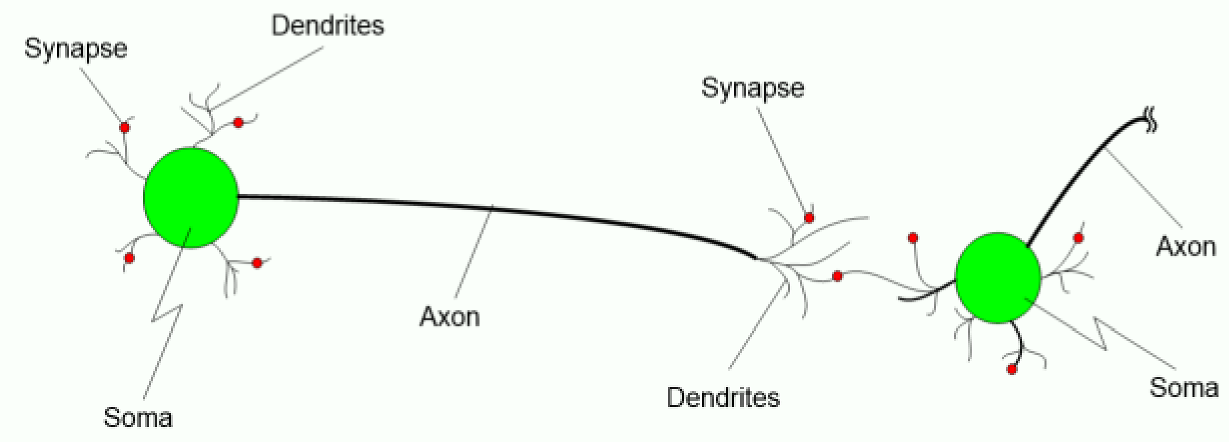


Artificial Intelligence (AI)	• Broadest concept: any technique enabling computers to mimic human intelligence
Machine Learning (ML)	• Subset of AI: systems learn patterns from data instead of explicit programming
Deep Learning (DL)	• Subset of ML: uses neural networks with multiple layers ("deep") • Revolutionized AI in the past decade
Artificial Neural Networks (ANNs)	• Foundation of Deep Learning • Computational models inspired by biological neural networks
Generative AI	• Creates new content (text, code, images) • Uses transformer architectures (e.g., ChatGPT, Claude)

Fundamentals of Artificial Neural Networks

Basic Architecture of Artificial Neural Networks

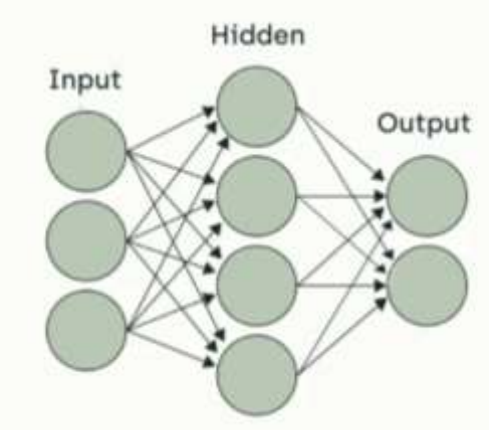




Biological Neuron

Artificial Neuron:

- Receives multiple inputs (x_1, x_2, x_3...)
- Each input multiplied by weight (w_1, w_2, w_3...)
- Weighted inputs summed together
- Bias term added
- Result passes through activation function

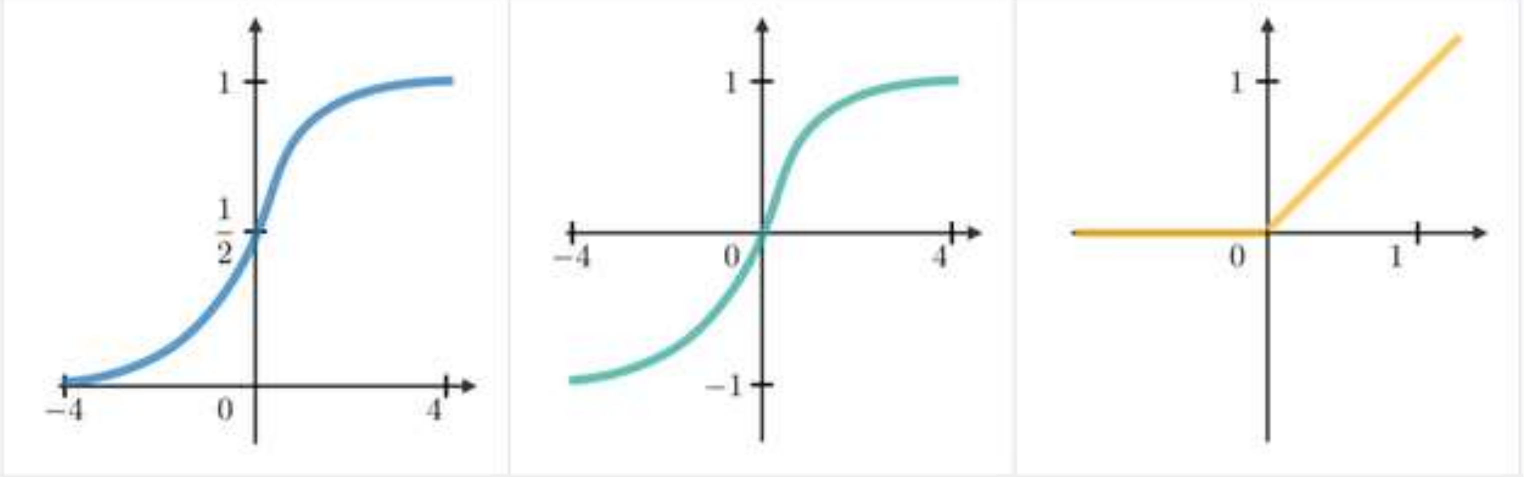


Network Layers:

- Input layer: receives raw data
- Hidden layers: intermediate computations and feature extraction
- Output layer: produces final predictions

Activation Functions

Sigmoid	Tanh	ReLU
$g(z) = \dfrac{1}{1+e^{-z}}$	$g(z) = \dfrac{e^{z}-e^{-z}}{e^{z}+e^{-z}}$	$g(z) = \max(0, z)$



Why activation functions?

- Without them: network only computes linear transformations
- Real-world problems need curves, bends, sophisticated boundaries
- Activation functions introduce non-linearity
- Enable networks to approximate any complex relationship

Sigmoid

S-shaped curve, squashes input to range (0, 1)

Useful for outputs as probabilities

Tanh (Hyperbolic Tangent)

Similar to sigmoid, outputs range (-1, 1)

Zero-centered: often works better in hidden layers

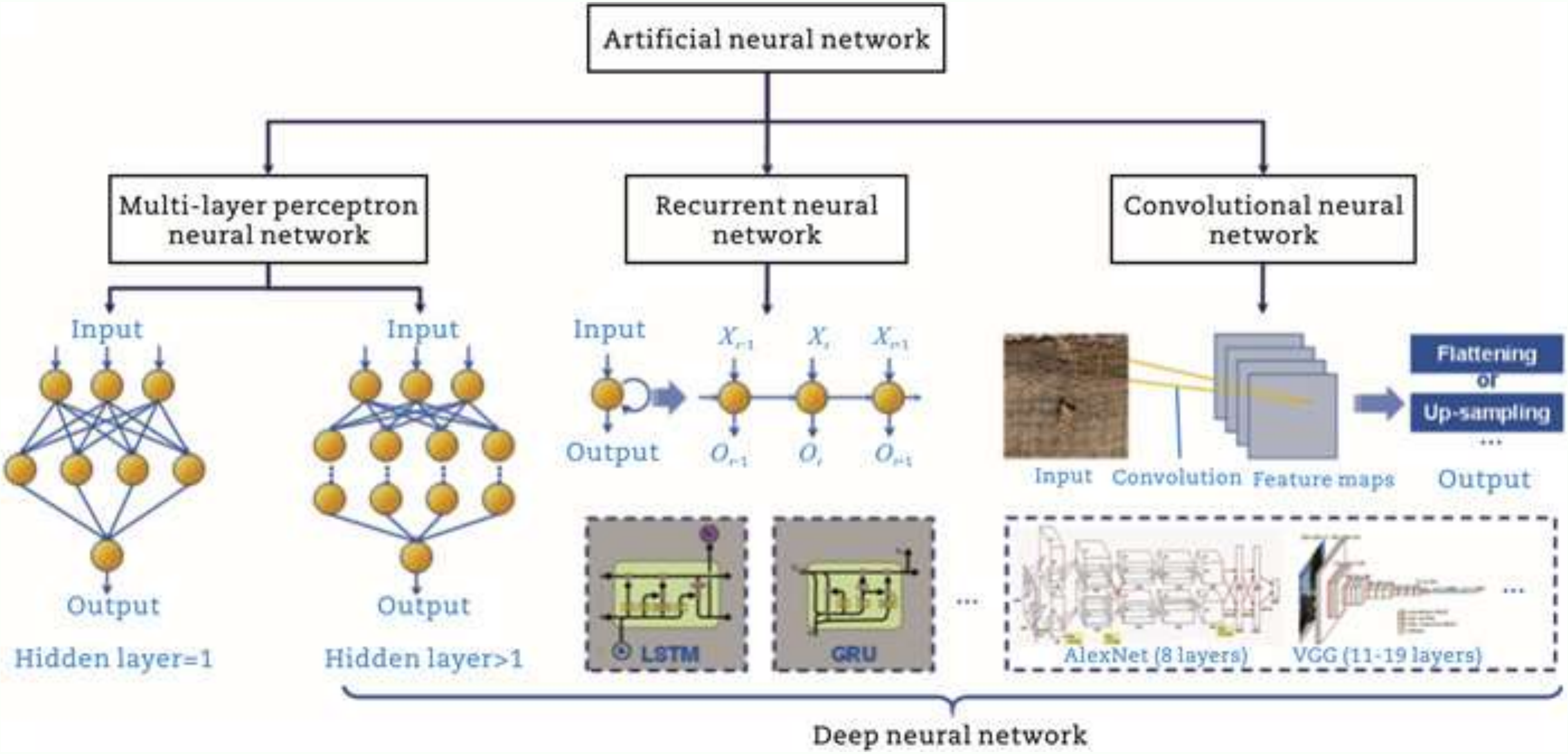
ReLU (Rectified Linear Unit)

Most popular for hidden layers

$f(z) = \max(0, z)$

Simple yet remarkably effective

Architecture Types



Types of Learning

Supervised Learning

- Learning with labeled data (input-output pairs, correct answer known)
- Network compares predictions to true answers
- Adjusts to minimize errors

Unsupervised Learning

- Learning from unlabeled data
- Network discovers patterns without being told what to look for
- Techniques: clustering, anomaly detection
- Useful when you don't know in advance what kinds of faults might occur

Reinforcement Learning

- Learning through interaction
- Agent takes actions, receives rewards or penalties
- Learns which actions lead to desirable outcomes
- Powerful for sequential decision-making tasks

Note : The Supervised and Unsupervised learning methods are most popular forms of learning compared to Reinforced learning

Fundamentals of Artificial Neural Networks

Key Training Concepts

Overfitting

Network learns training data too well

Memorizes it, including noise and peculiarities

Rather than learning general patterns

Causes:

- Network architecture too complex for available data
- Training continues for too long
- Insufficient training data
- Lack of regularization techniques

Consequences:

- Excellent performance on training data
- Poor performance on new, unseen data

Underfitting

Network too simple or hasn't trained enough

Fails to capture important patterns

Poor performance even on training data

The Goal

- Network complex enough to learn meaningful patterns
- Not so complex that it memorizes noise
- Balance crucial for models that generalize to real-world applications

Renewable Energy Systems

Types of Renewable Energy Sources

Solar Energy

Converts sunlight to electricity (PV panels) or concentrates solar heat

Intermittent (only works when sun shines)

Variable (depends on cloud cover, time of day, season)

Wind Energy

Turbines convert wind's kinetic energy to electricity

Variable and intermittent

Turbines generate when wind blows within specific speed ranges

Hydropower

Harnesses energy from flowing or falling water

Most mature renewable technology

Other sources

Biomass, geothermal, ocean energy (waves, tides, thermal gradients)

Hybrid systems

Combine multiple sources with energy storage

Improve reliability and dispatchability

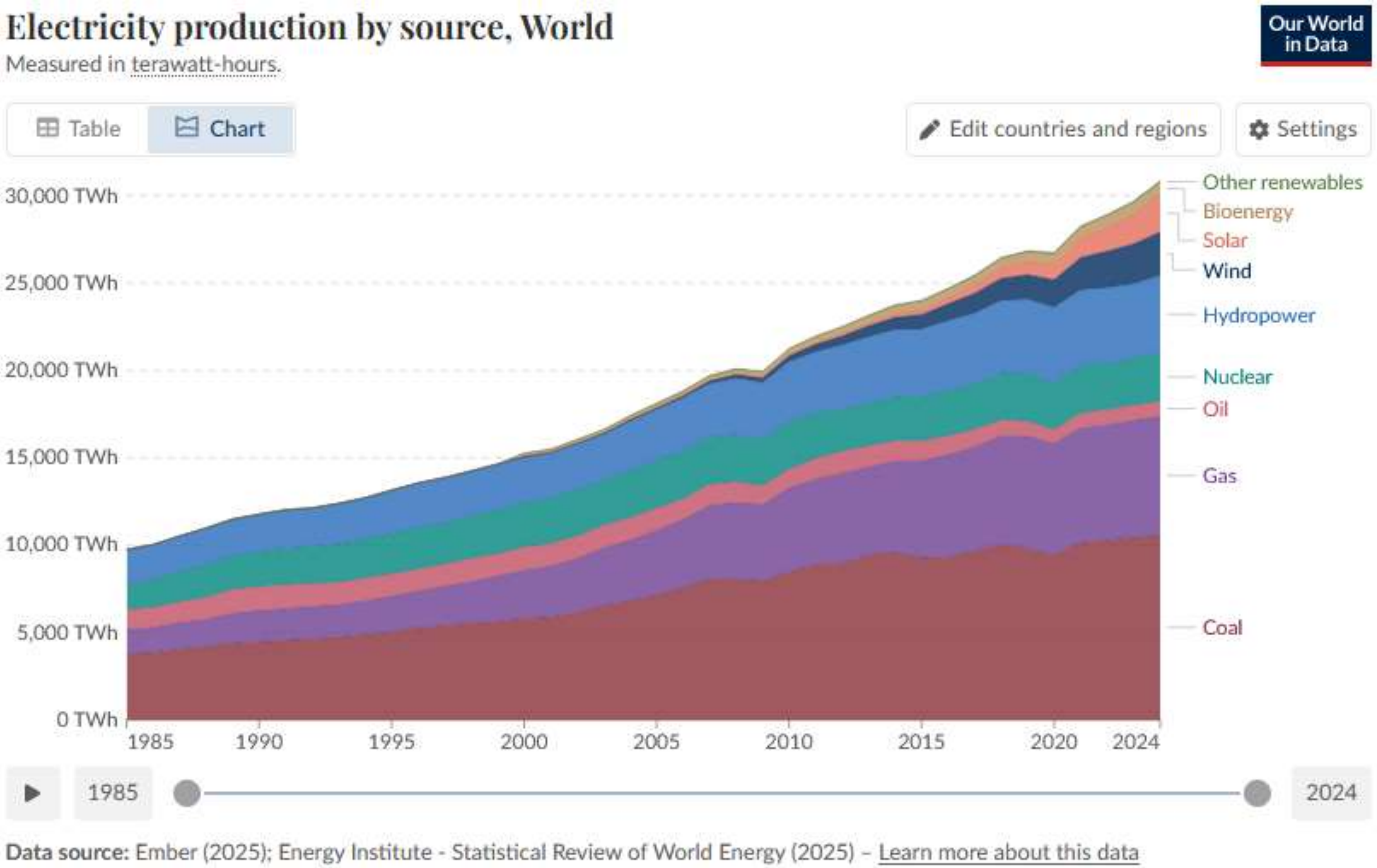
Renewable Energy Systems

Trends in Renewable Energy

19%	30%	90%	70%
2000	**2023**	**Solar PV**	**Wind**
Renewables share of global electricity	Renewables share of global electricity	Installation cost reduction since 2010	Turbine cost reduction since 2010

Results

- Solar and wind are now among the most competitive sources of new electricity generation
- Creating jobs in manufacturing, installation, and maintenance



Renewable Energy Systems

Challenges Addressable by ANNs

Forecasting Generation

Solar and wind output varies with weather conditions, making accurate prediction difficult. Grid operators need reliable forecasts hours to days ahead to balance supply and demand, schedule conventional generation, and participate in electricity markets. Inaccurate forecasts lead to economic losses and grid instability.

Equipment Diagnostics

Renewable installations operate in harsh environments. Early detection of developing faults allows proactive maintenance, preventing costly failures and extending equipment life. The challenge lies in identifying subtle fault signatures in complex sensor data.

System Optimization

Maximum Power Point Tracking (MPPT) ensures solar panels and wind turbines extract maximum available energy despite continuously changing conditions. Traditional methods work but can be slow to respond or get trapped at suboptimal operating points.

Why ANNs excel: These challenges involve complex, non-linear relationships between many variables, require processing large volumes of sensor data, and benefit from learning patterns from historical experience.

Energy Forecasting

Solar Energy Forecasting

Inputs:

Current and historical solar irradiance, temperature, humidity, cloud cover, wind conditions, historical power output, time-related features

Outputs:

Power generation forecasts (short-term: minutes to hours; day-ahead)

Challenges:

Variable irradiance depends on cloud cover, time of day, season, atmospheric conditions

Architectures:

- MLPs commonly used
- LSTMs capture temporal dependencies
- CNNs process satellite imagery and sky camera images to predict cloud movements and irradiance changes
- ANNs incorporate NWP model outputs for day-ahead forecasts, learn to correct biases and downscale to specific locations

Wind Energy Forecasting

Inputs:

Recent wind speed and direction, atmospheric conditions, historical power output, turbulence intensity; for longer horizons: NWP model outputs; data from multiple locations

Outputs:

Power generation forecasts (short-term; day-ahead for market participation)

Challenges:

Turbulent, rapidly changing nature; generation only within cut-in to cut-out speeds

Architectures:

- LSTMs excel at modeling temporal dynamics and temporal correlation
- ANNs consider data from upstream weather stations or wind farms
- ANNs post-process NWP outputs, correct systematic errors based on historical performance

Hydropower Forecasting

Inputs:

Historical streamflow, precipitation (observed and forecasted), snow water equivalent, temperature, reservoir levels, soil moisture, climate indices

Outputs:

Streamflow predictions into reservoirs (short-term for run-of-river; seasonal for reservoir-based)

Challenges:

Complex non-linear hydrological relationships: precipitation-streamflow connection involves soil conditions, vegetation, topography, seasonal variations

Architectures:

ANNs learn to approximate these complex relationships from historical data

Fault Detection and Diagnostics

Solar Photovoltaic Systems

Inputs:

Current-voltage characteristics, power output patterns, temperatures, solar irradiance, string currents and voltages

Outputs:

Fault classifications, anomaly alerts

Common faults:

- Partial shading and soiling
- Module degradation and hotspots
- Inverter failures
- Connection problems
- Ground faults

Architectures:

- MLPs classify specific fault types based on operational signatures
- Autoencoders compress and reconstruct input data (reconstruction error spikes when faults occur)
- CNNs analyze thermal images of solar panels, detect hotspots and thermal anomalies
- LSTMs learn normal aging patterns, detect gradual degradation

Wind Turbines

Inputs:

Vibration signals, acoustic emissions, oil temperature, SCADA data (power output, rotor speed, temperatures, wind speed), current and voltage

Outputs:

Fault classifications, maintenance alerts

Common faults:

- Gearbox problems
- Generator faults
- Blade damage
- Bearing failures
- Pitch system malfunctions

Architectures:

- CNNs analyze spectrograms (visual representations of vibration frequencies over time), recognize fault-specific patterns
- LSTMs analyze long-term SCADA data trends, learn normal relationships between variables, detect drifts
- Autoencoders trained on healthy turbine data detect multivariate anomalies

Hydropower Plants

Inputs:

Vibration and acoustic signatures, bearing temperatures, generator partial discharge activity, efficiency trends, water quality

Outputs:

Condition classifications, wear trend predictions

Common faults:

- Turbine cavitation and erosion
- Bearing wear
- Generator insulation degradation
- Mechanical seal problems

Architectures:

- Feedforward networks classify operating conditions, associate with expected vibration or temperature signatures
- LSTMs track long-term trends indicating gradual wear (e.g., turbine efficiency decreases slowly due to erosion; accelerated loss indicates cavitation damage)

Additional Applications

Maximum Power Point Tracking (MPPT)

Solar panels and wind turbines have optimal operating points that shift with environmental changes. ANNs can learn complex mappings between conditions and optimal settings. For solar systems under partial shading, ANNs' non-linear capability helps navigate power-voltage curves with multiple peaks. For wind turbines, ANNs output optimal generator torque or rotor speed as wind fluctuates. While well-tuned conventional MPPT algorithms perform effectively, ANNs provide incremental improvements, particularly in complex scenarios.

Load Forecasting

Predicting electricity demand complements generation forecasting for grid management. ANNs forecast consumption based on historical patterns, weather, time factors, and socio-economic indicators.

Resource Assessment

Before installing systems, ANNs estimate long-term average solar irradiance or wind speed at candidate sites using limited measurement data, topographical features, and correlations with nearby locations, reducing assessment time and cost.

System Optimization

ANNs approximate optimal control strategies for real-time operation of renewable systems and hybrid configurations, learning to adjust parameters to improve energy output, economic return, or equipment longevity.

Power Quality Management

ANNs help predict power quality events and determine corrective actions like reactive power compensation or storage dispatch.

Hybrid and Ensemble Approaches

Ensemble Methods

- Train multiple neural networks with different architectures or initializations and combine their predictions through averaging or voting. Ensembles improve accuracy and robustness.
- Example for wind forecasting: combine LSTM for temporal patterns, feedforward network for statistical features, CNN for weather imagery

Hybrid Architectures

- Connect different network types
- CNN-LSTM hybrids: CNN layers extract spatial features from weather maps → feed into LSTM layers modeling temporal dynamics
- Autoencoder-classifier combinations: first learn efficient representations → then classify for fault diagnosis

Integrating with Other Techniques

- Adaptive Neuro-Fuzzy Inference Systems (ANFIS) combine neural learning with fuzzy logic reasoning, providing interpretable rules while optimizing from data
- Valuable when expert knowledge exists but exact relationships are uncertain

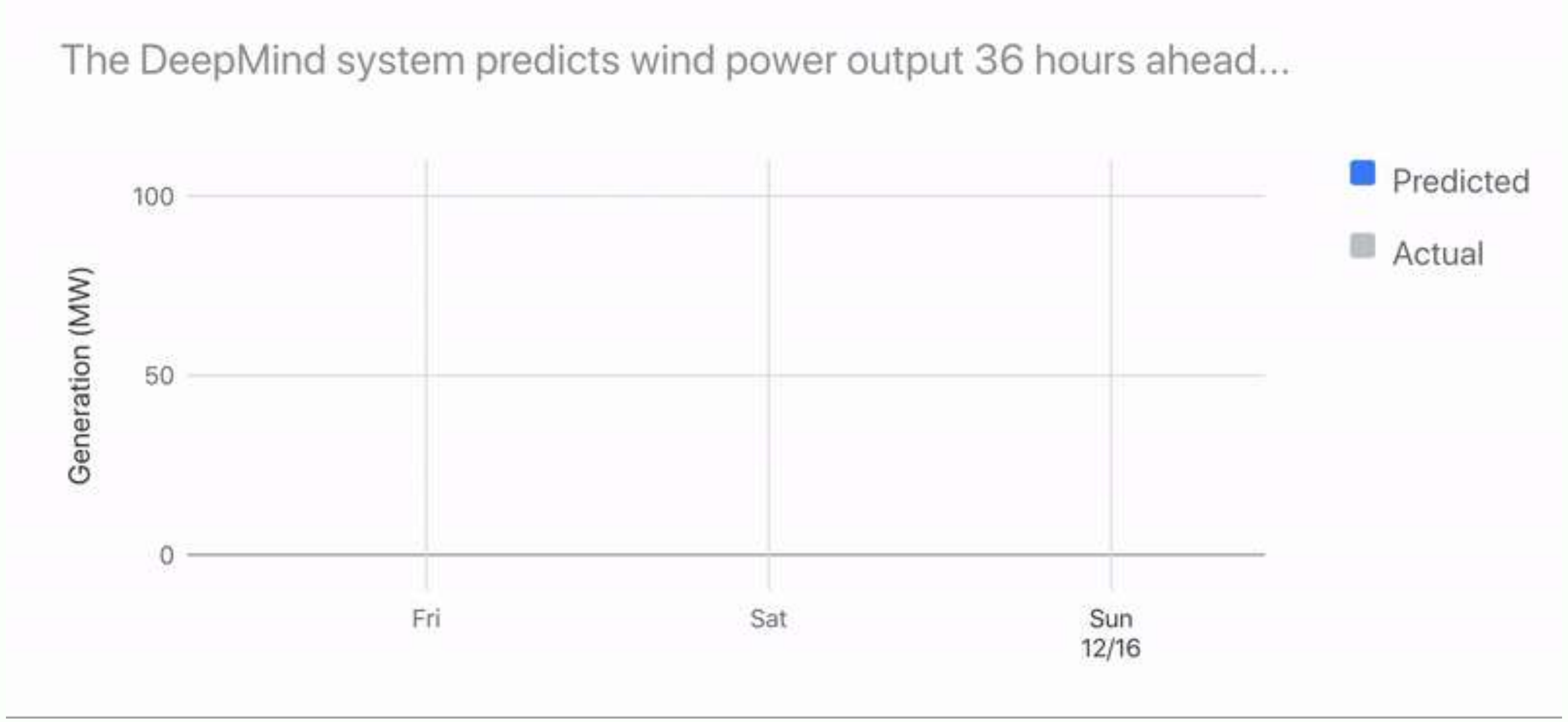
Combining with Physical Models

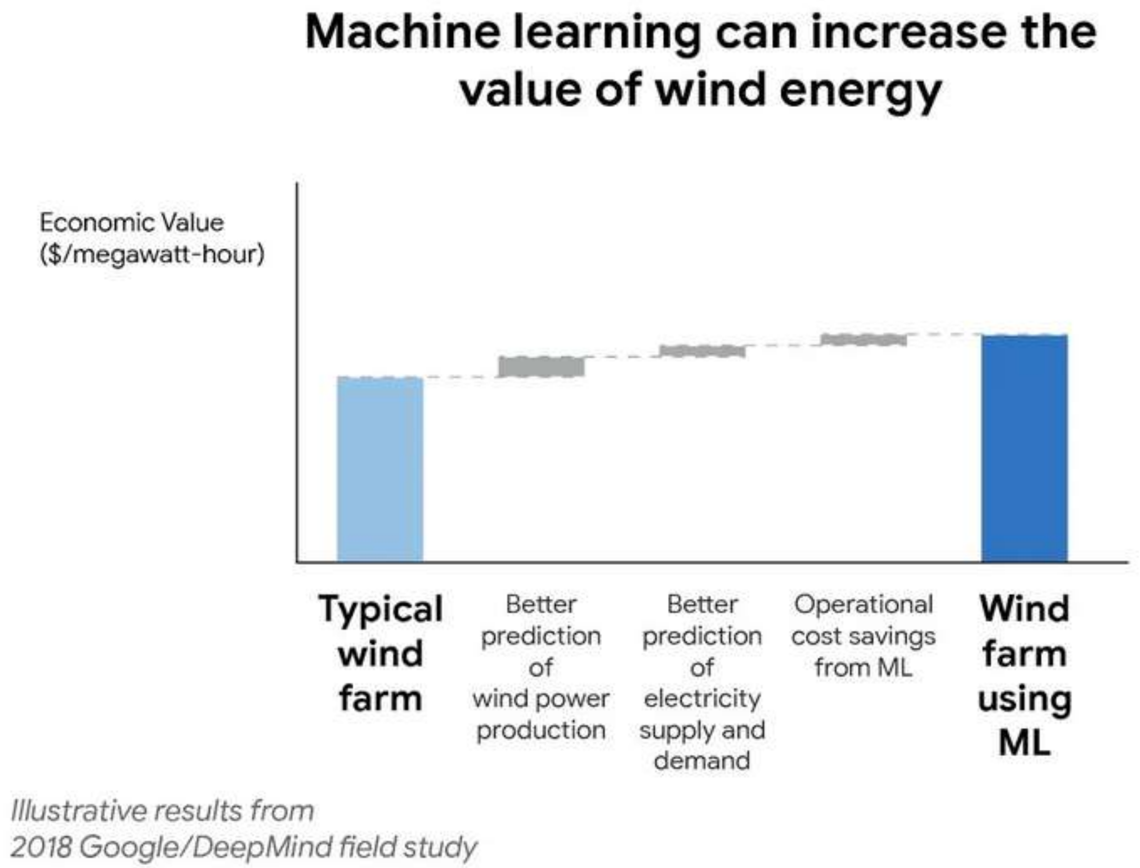
- Post-processing Numerical Weather Prediction with ANNs widely used operationally
- NWP provides physically consistent forecasts, while ANNs learn to correct biases and downscale to specific locations, combining physics with statistical learning.

Real World Applications of ANNs for Renewable Energy Systems

DeepMind (a subsidiary of Google) - Wind Energy Forecasting

Location: United States (central region)
Scale: ~700 MW of wind power capacity
Deployed since: ~2018
Application: Predict 36-hour-ahead wind power output
Result: ~20% increase in economic value of the wind energy portfolio
Architecture: Deep neural network (possibly LSTMs or hybrid architectures) trained on years of historical data; inputs: weather forecasts and historical turbine data; output: 36-hour power forecasts





Real World Applications of ANNs for Renewable Energy Systems

Siemens Gamesa Renewable Energy (SGRE) - Wind Turbine Blade Inspection

Location: Denmark (Aalborg), United Kingdom (Hull), etc.
Scale: ~5000 turbines installed
Deployed since: ~2017
Application: Automated analysis of blade inspection data (drone images and ultrasonic scans) to detect defects
Result: Inspection time reduced up to ~75% (cuts inspection times for windmill turbine blades from 6 hours to just 1.5 hours, resulting in significant cost savings)
Architecture: most likely CNN; inputs: high-resolution blade images and scan data; output: defect classifications and locations

State Power Investment Corporation (SPIC) - Hydropower Smart O&M

Location: China (Hunan Province), Wuqiangxi and Jinweizhou plants
Scale: Wuqiangxi: 1200 MW; Jinweizhou: 63.18 MW
Deployed since: November 2020
Application: Smart remote O&M using AI diagnostics, condition monitoring, and lifetime prediction
Result: ~10% reduction in maintenance costs; +0.5% power production time; +0.3% generation
Architecture: Neural networks in edge-cloud architecture; inputs: image, sound, thermal data from robots/drones; outputs: diagnostics, lifetime prognosis, maintenance suggestions

Conclusions

Key Insights

- ANNs have matured into practical tools addressing real renewable energy challenges
- We've seen how ANNs fit within the broader Artificial Intelligence landscape as the foundation of deep learning, and how their fundamental architecture - layers of interconnected neurons with weights, biases, and activation functions -- enables learning complex patterns from data.

Main Limitations

- Data requirements: need substantial quality data for training
- Models are location-specific
- Computational complexity: training deep networks demands significant resources
- "Black box" problem: understanding why networks make predictions is challenging
- Sensitivity to input quality: sensor drift or novel conditions cause unexpected predictions
- Need for regular retraining: system characteristics change over time
- Overfitting risks: complex networks may memorize rather than generalize

Future Outlook

- As renewable energy penetration increases globally, the ANNs field continues evolving with newer architectures, improved training methods, and better integration with physical models.

Thank You

Questions?